Importing the relevant libraries

```
!pip install dmba
```

```
Requirement already satisfied: dmba in /usr/local/lib/python3.11/dist-packages (0.2.4)
Requirement already satisfied: graphviz in /usr/local/lib/python3.11/dist-packages (from dmba) (0.20.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from dmba) (3.10.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from dmba) (2.0.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (from dmba) (2.2.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (from dmba) (1.6.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from dmba) (1.14.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (4.57.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (11.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (2.8.
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas->dmba) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas->dmba) (2025.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->dmba) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->dmba) (3.
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib->d
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from dmba import classificationSummary, forward_selection, backward_elimination, gainsChart, liftChart
from dmba import AIC_score, BIC_score
from dmba import plotDecisionTree
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEncoder
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, roc_curve
```

```
Colab environment detected.
```

Loading the loan dataset

```
df = pd.read_csv('/content/loan_data.csv')
df.head()
```

	person_age	person_gender	person_education	person_income	person_emp_exp	person_home_ownership	loan_amnt	loan_intent
0	22.0	female	Master	71948.0	0	RENT	35000.0	PERSONAL
1	21.0	female	High School	12282.0	0	OWN	1000.0	EDUCATION
2	25.0	female	High School	12438.0	3	MORTGAGE	5500.0	MEDICAL
3	23.0	female	Bachelor	79753.0	0	RENT	35000.0	MEDICAL
4	24.0	male	Master	66135.0	1	RENT	35000.0	MEDICAL

Next steps: Generate code with df View recommended plots New interactive sheet

Data Exploration

```
df.shape
```

```
(45000, 14)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45000 entries, 0 to 44999
Data columns (total 14 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   person_age                      45000 non-null  float64
 1   person_gender                   45000 non-null  object 
 2   person_education                45000 non-null  object 
 3   person_income                   45000 non-null  float64
 4   person_emp_exp                  45000 non-null  int64  
 5   person_home_ownership           45000 non-null  object 
 6   loan_amnt                       45000 non-null  float64
 7   loan_intent                     45000 non-null  object 
 8   loan_int_rate                   45000 non-null  float64
 9   loan_percent_income             45000 non-null  float64
 10  cb_person_cred_hist_length      45000 non-null  float64
 11  credit_score                    45000 non-null  int64  
 12  previous_loan_defaults_on_file  45000 non-null  object 
 13  loan_status                     45000 non-null  int64  
dtypes: float64(6), int64(3), object(5)
memory usage: 4.8+ MB
```

```
df.describe()
```

	person_age	person_income	person_emp_exp	loan_amnt	loan_int_rate	loan_percent_income	cb_person_cred_hist_length
count	45000.000000	4.500000e+04	45000.000000	45000.000000	45000.000000	45000.000000	45000.000000
mean	27.764178	8.031905e+04	5.410333	9583.157556	11.006606	0.139725	5.867489
std	6.045108	8.042250e+04	6.063532	6314.886691	2.978808	0.087212	3.879702
min	20.000000	8.000000e+03	0.000000	500.000000	5.420000	0.000000	2.000000
25%	24.000000	4.720400e+04	1.000000	5000.000000	8.590000	0.070000	3.000000
50%	26.000000	6.704800e+04	4.000000	8000.000000	11.010000	0.120000	4.000000
75%	30.000000	9.578925e+04	8.000000	12237.250000	12.990000	0.190000	8.000000
max	144.000000	7.200766e+06	125.000000	35000.000000	20.000000	0.660000	30.000000

```
df.isna().sum()
```

	0
person_age	0
person_gender	0
person_education	0
person_income	0
person_emp_exp	0
person_home_ownership	0
loan_amnt	0
loan_intent	0
loan_int_rate	0
loan_percent_income	0
cb_person_cred_hist_length	0
credit_score	0
previous_loan_defaults_on_file	0
loan_status	0

dtype: int64

```
df.duplicated().sum()
```

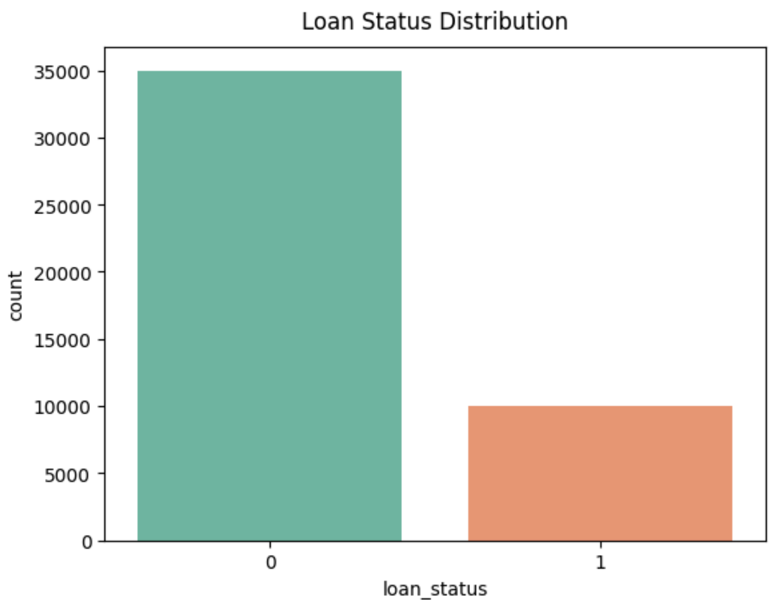
```
np.int64(0)
```

```
df.rename({'person_age': 'age', 'person_gender': 'gender', 'person_education': 'education', 'person_home_ownership': 'home_owner
```

```
df.columns
```

```
Index(['age', 'gender', 'education', 'income', 'employment_experience',
       'home_ownership', 'loan_amount', 'loan_intent', 'loan_interest_rate',
       'loan_percent_income', 'cb_person_cred_hist_length', 'credit_score',
       'previous_loan_defaults_on_file', 'loan_status'],
      dtype='object')
```

```
sns.countplot(x='loan_status', data=df, palette='Set2')
plt.title('Loan Status Distribution', pad=10)
plt.show();
```



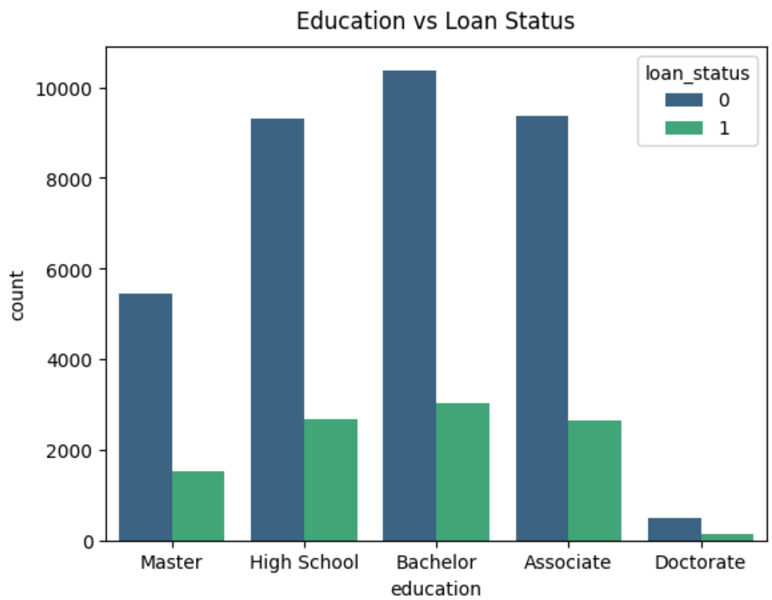
It is clearly evident from the above plot that the target binary classes are significantly imbalanced. This may adversely affect the performance of machine learning models.

```
df.education.value_counts()
```

education	count
Bachelor	13399
Associate	12028
High School	11972
Master	6980
Doctorate	621

dtype: int64

```
sns.countplot(x='education', data=df, hue='loan_status', palette='viridis')
plt.title('Education vs Loan Status', pad=10)
plt.show();
```



Data Preprocessing

```
# Ordinal Encoding
education_encoder = OrdinalEncoder(categories=[['High School','Associate','Bachelor','Master','Doctorate']], dtype=int)
df.education = education_encoder.fit_transform(df[['education']])
df.education.value_counts()
```

education	count
2	13399
1	12028
0	11972
3	6980
4	621

dtype: int64

```
cat_cols = ['gender','home_ownership','loan_intent','previous_loan_defaults_on_file']

# One-hot encoding
def one_hot_encode(data,column):
  encoder = OneHotEncoder(sparse_output=False, drop='first', handle_unknown='ignore')
  encoded_data = encoder.fit_transform(data[[column]])
  encoded_df = pd.DataFrame(encoded_data, columns=encoder.get_feature_names_out())
  data = pd.concat([data,encoded_df],axis=1)
  data.drop(column, axis=1, inplace=True)
  return data


for col in cat_cols:
  df = one_hot_encode(df,col)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45000 entries, 0 to 44999
Data columns (total 20 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   age                             45000 non-null  float64
 1   education                       45000 non-null  int64
 2   income                          45000 non-null  float64
 3   employment_experience           45000 non-null  int64
 4   loan_amount                     45000 non-null  float64
 5   loan_interest_rate              45000 non-null  float64
```

```
 6   loan_percent_income             45000 non-null  float64
 7   cb_person_cred_hist_length      45000 non-null  float64
 8   credit_score                    45000 non-null  int64
 9   loan_status                     45000 non-null  int64
 10  gender_male                     45000 non-null  float64
 11  home_ownership_OTHER            45000 non-null  float64
 12  home_ownership_OWN              45000 non-null  float64
 13  home_ownership_RENT             45000 non-null  float64
 14  loan_intent_EDUCATION           45000 non-null  float64
 15  loan_intent_HOMEIMPROVEMENT     45000 non-null  float64
 16  loan_intent_MEDICAL             45000 non-null  float64
 17  loan_intent_PERSONAL            45000 non-null  float64
 18  loan_intent_VENTURE             45000 non-null  float64
 19  previous_loan_defaults_on_file_Yes  45000 non-null  float64
dtypes: float64(16), int64(4)
memory usage: 6.9 MB
```

Feature Splitting (Train-Test Split)

```
X = df.drop('loan_status', axis=1)
y = df['loan_status']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Feature Selection

Backward Elimination

```
def train_model(variables):
    model = LogisticRegression(solver='liblinear')
    model.fit(X_train[list(variables)], y_train)
    return model
```

```
def score_model(model, variables):
    return AIC_score(y_train, model.predict_proba(X_train[variables])[:, 1], model)
```

```
allVariables = X_train.columns

# Backward elimination
back_model, back_variables = backward_elimination(allVariables, train_model, score_model, verbose=True)

# Summary on validation set
classificationSummary(y_test, back_model.predict(X_test[back_variables]))
```

```
Variables: age, education, income, employment_experience, loan_amount, loan_interest_rate, loan_percent_income, cb_person_cr
Start: score=26584.82
Step: score=13816.57, remove income
Step: score=8628.74, remove loan_amount
Step: score=8626.35, remove age
Step: score=8623.71, remove loan_intent_HOMEIMPROVEMENT
Step: score=8623.71, remove None
Confusion Matrix (Accuracy 0.8873)

       Prediction
Actual    0    1
     0 6542  448
     1  566 1444
```

Forward Selection

```
def train_model_forward(variables):
    if len(variables) == 0:
        return None
    model = LogisticRegression(solver='liblinear')
    model.fit(X_train[list(variables)], y_train)
    return model
```

```
def score_model_forward(model, variables):
    if len(variables) == 0:
        return AIC_score(y_train, [y_train.mean()] * len(y_train), model, df=1)
    return AIC_score(y_train, model.predict_proba(X_train[variables])[:, 1], model)


# Forward selection
fwd_model, fwd_variables = forward_selection(X_train.columns, train_model_forward, score_model_forward, verbose=True)

# Summary on validation set
classificationSummary(y_test, fwd_model.predict(X_test[fwd_variables]))
```

```
Variables: age, education, income, employment_experience, loan_amount, loan_interest_rate, loan_percent_income, cb_person_cr
Start: score=38941.30, constant
Step: score=26441.48, add previous_loan_defaults_on_file_Yes
Step: score=19150.26, add loan_percent_income
Step: score=13251.13, add loan_interest_rate
Step: score=11242.09, add home_ownership_RENT
Step: score=10083.63, add credit_score
Step: score=9637.10, add loan_intent_VENTURE
Step: score=9235.83, add loan_intent_EDUCATION
Step: score=8955.70, add loan_intent_PERSONAL
Step: score=8710.95, add home_ownership_OWN
Step: score=8666.07, add employment_experience
Step: score=8638.88, add loan_intent_MEDICAL
Step: score=8628.75, add home_ownership_OTHER
Step: score=8622.39, add age
Step: score=8622.39, add None
Confusion Matrix (Accuracy 0.8877)

       Prediction
Actual    0    1
     0 6542  448
     1  563 1447
```

```
print("Variables selected by Backward Elimination:")
print(back_variables)

print("\nVariables selected by Forward Selection:")
print(fwd_variables)
```

```
Variables selected by Backward Elimination:
['education', 'employment_experience', 'loan_interest_rate', 'loan_percent_income', 'cb_person_cred_hist_length', 'credit_sc

Variables selected by Forward Selection:
['previous_loan_defaults_on_file_Yes', 'loan_percent_income', 'loan_interest_rate', 'home_ownership_RENT', 'credit_score', '
```

```
selected_variables = list(set(back_variables).intersection(set(fwd_variables)))
print("Selected Variables:")
print(selected_variables)
```

```
Selected Variables:
['loan_intent_PERSONAL', 'loan_percent_income', 'credit_score', 'loan_intent_VENTURE', 'loan_intent_EDUCATION', 'employment_
```

```
len(selected_variables), X_train.shape[1]
```

```
(12, 19)
```

We reduced the number of predictor variables significantly from 19 to 12.

```
final_X_train = X_train[selected_variables]
final_X_test = X_test[selected_variables]
```

```
# Feature Scaling
scaler = StandardScaler()
scaled_X_train = scaler.fit_transform(final_X_train)
scaled_X_test = scaler.transform(final_X_test)
```

Model Training & Evaluation

Logistic Regression

```
# Logistic Regression
logit_reg = LogisticRegression(penalty='l2',C=1e42, solver='liblinear')
logit_reg.fit(scaled_X_train, y_train)
```

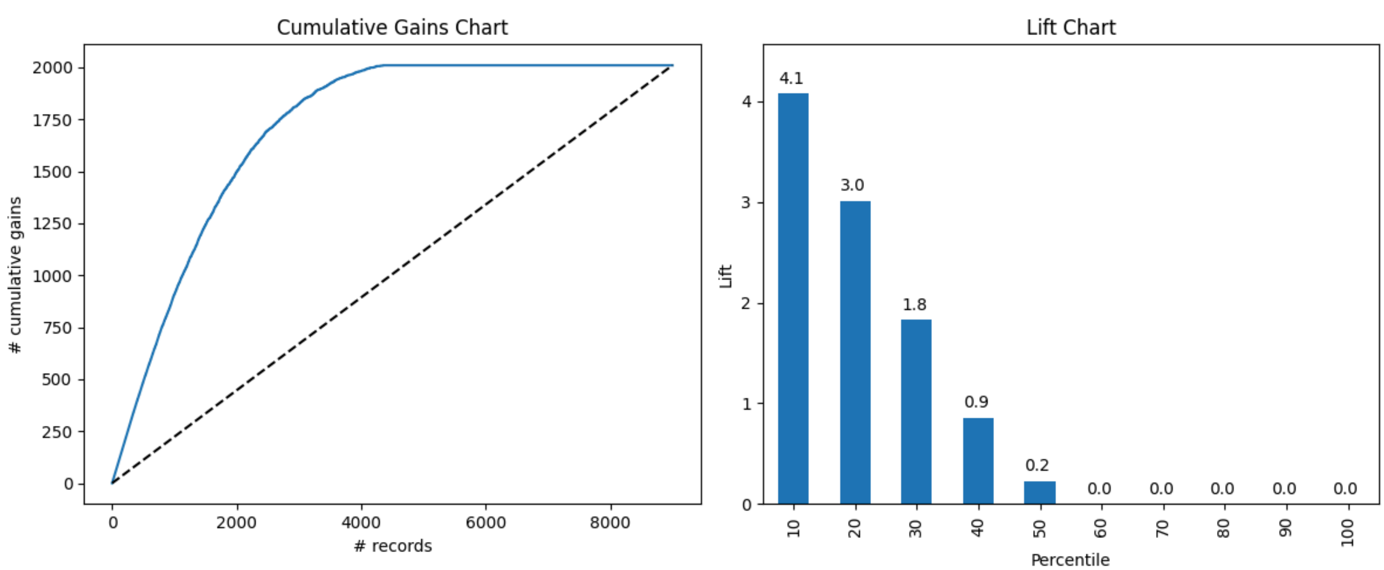
```
LogisticRegression
LogisticRegression(C=1e+42, solver='liblinear')
```

```
# Predictions
logit_pred_train = logit_reg.predict(scaled_X_train)
logit_pred_test = logit_reg.predict(scaled_X_test)


lr_probs = logit_reg.predict_proba(scaled_X_test)[:, 1]


lr_results_df = pd.DataFrame({
    'actual': y_test,
    'p(1)': lr_probs
}).sort_values(by='p(1)', ascending=False)
lr_results_df.head()
```

	actual	p(1)
596	1	0.999176
43457	1	0.997378
4	1	0.997277
42975	1	0.997039
29278	1	0.997033

Next steps: Generate code with lr_results_df View recommended plots New interactive sheet

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
gainsChart(lr_results_df['actual'], ax=axes[0])
liftChart(lr_results_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title("Cumulative Gains Chart")
axes[1].set_title("Lift Chart")
plt.tight_layout()
plt.show()
```




```
# Evaluation
print("Logistic Regression - Training Set")
classificationSummary(y_train, logit_pred_train)
```

```
print("\nLogistic Regression - Test Set")
classificationSummary(y_test, logit_pred_test)
```

```
Logistic Regression - Training Set
Confusion Matrix (Accuracy 0.8922)

       Prediction
Actual     0     1
     0 26230  1780
     1  2101  5889

Logistic Regression - Test Set
Confusion Matrix (Accuracy 0.8874)

       Prediction
Actual    0    1
     0 6543  447
     1  566 1444
```

```
print("AIC:", AIC_score(y_test, logit_pred_test, df=scaled_X_train.shape[1]+1))
print("BIC:", BIC_score(y_test, logit_pred_test, df=scaled_X_train.shape[1]+1))
```

```
AIC: 5910.118429057053
BIC: 6009.58814704551
```

CART

```
# CART model
cart_model = DecisionTreeClassifier(max_depth=6,random_state=42)
cart_model.fit(final_X_train, y_train) # no scaling needed for trees
```

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=6, random_state=42)
```

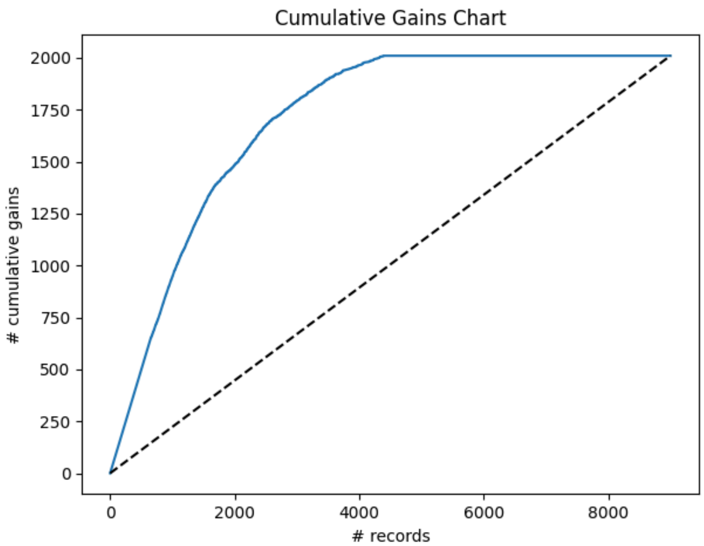
```
# Predictions
cart_pred_train = cart_model.predict(final_X_train)
cart_pred_test = cart_model.predict(final_X_test)
```

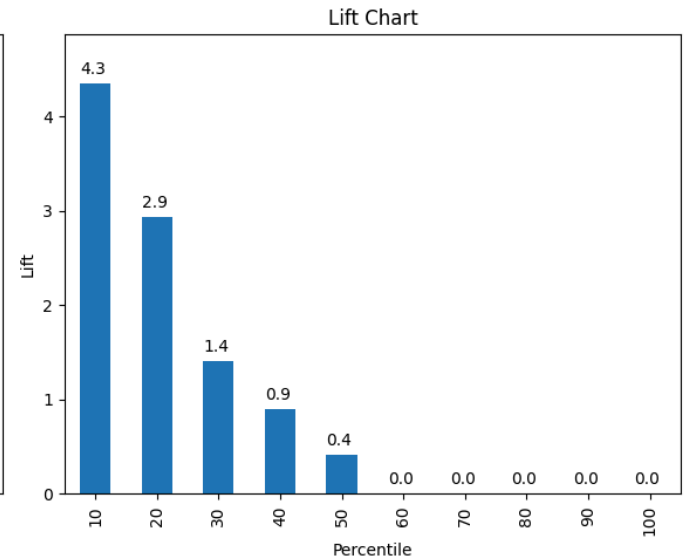
```
cart_probs = cart_model.predict_proba(final_X_test)[:, 1]

cart_results_df = pd.DataFrame({
    'actual': y_test,
    'p(1)': cart_probs
}).sort_values(by='p(1)', ascending=False)
cart_results_df.head()
```

	actual	p(1)
43592	1	1.0
8473	1	1.0
14337	1	1.0
25118	1	1.0
44371	1	1.0

Next steps: Generate code with cart_results_df | View recommended plots | New interactive sheet

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
gainsChart(cart_results_df['actual'], ax=axes[0])
liftChart(cart_results_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title("Cumulative Gains Chart")
axes[1].set_title("Lift Chart")
plt.tight_layout()
plt.show()
```





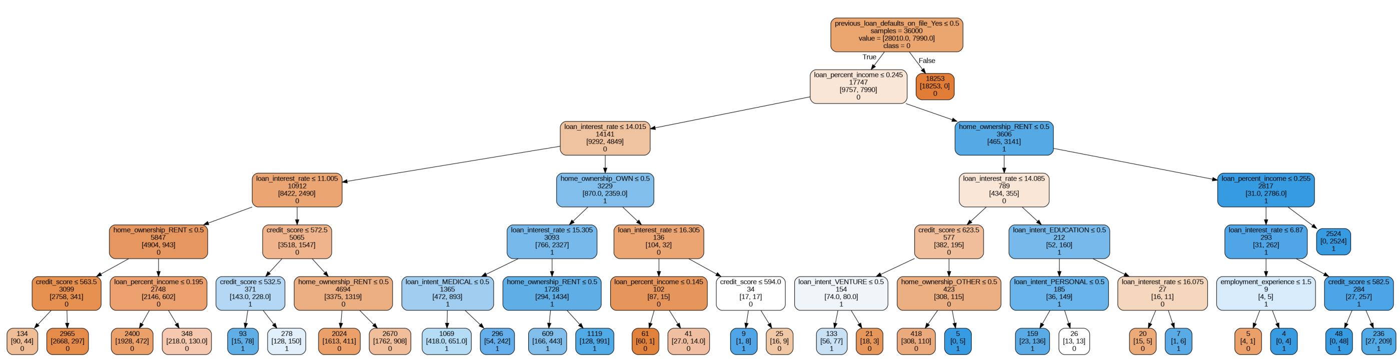

```
# Evaluation
print("CART - Training Set")
classificationSummary(y_train, cart_pred_train)

print("\nCART - Test Set")
classificationSummary(y_test, cart_pred_test)
```

```
CART - Training Set
Confusion Matrix (Accuracy 0.9046)

       Prediction
Actual     0     1
     0 26993  1017
     1  2418  5572

CART - Test Set
Confusion Matrix (Accuracy 0.8972)

       Prediction
Actual    0    1
     0 6690  300
     1  625 1385
```

```
print("AIC:", AIC_score(y_test, cart_pred_test, df=scaled_X_train.shape[1]+1))
print("BIC:", BIC_score(y_test, cart_pred_test, df=scaled_X_train.shape[1]+1))
```

```
AIC: 5092.218528430727
BIC: 5191.688246419184
```

```
# Visualize the Decision Tree
plotDecisionTree(cart_model, feature_names=final_X_train.columns.tolist(), class_names=['0', '1'])
```



Naive Bayes

```
# Naive Bayes
nb_model = GaussianNB()
nb_model.fit(scaled_X_train, y_train)
```

```
▾ GaussianNB
GaussianNB()
```

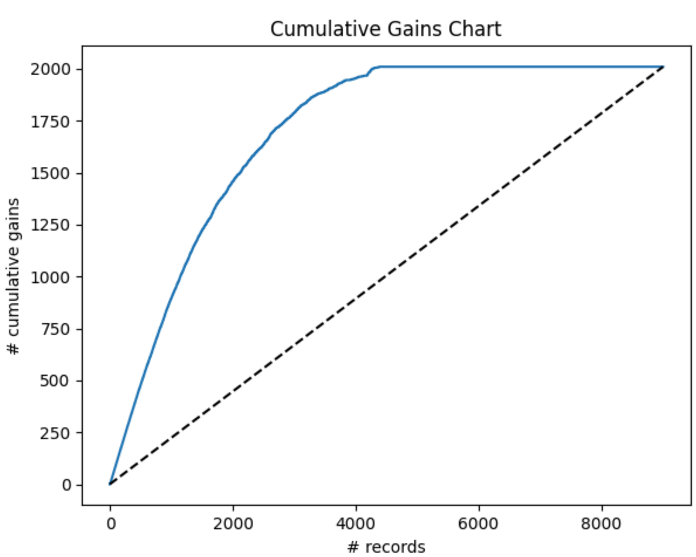
```
# Predictions
nb_pred_train = nb_model.predict(scaled_X_train)
nb_pred_test = nb_model.predict(scaled_X_test)
```

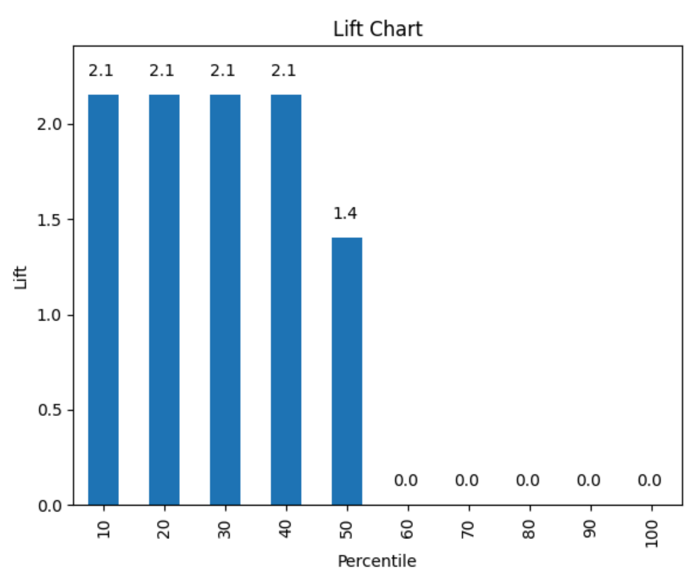
```
nb_probs = nb_model.predict_proba(scaled_X_test)[:, 1]

nb_results_df = pd.DataFrame({
    'actual': y_test,
    'p(1)': nb_probs
}).sort_values(by='p(1)', ascending=False)
nb_results_df.head()
```

	actual	p(1)
15983	0	1.0
31443	1	1.0
2351	0	1.0
6282	1	1.0
1503	1	1.0

Next steps: Generate code with nb_results_df | View recommended plots | New interactive sheet

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
gainsChart(nb_results_df['actual'], ax=axes[0])
liftChart(nb_results_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title("Cumulative Gains Chart")
axes[1].set_title("Lift Chart")
plt.tight_layout()
plt.show()
```





```
# Evaluation
print("Naive Bayes - Training Set")
classificationSummary(y_train, nb_pred_train)

print("\nNaive Bayes - Test Set")
classificationSummary(y_test, nb_pred_test)
```

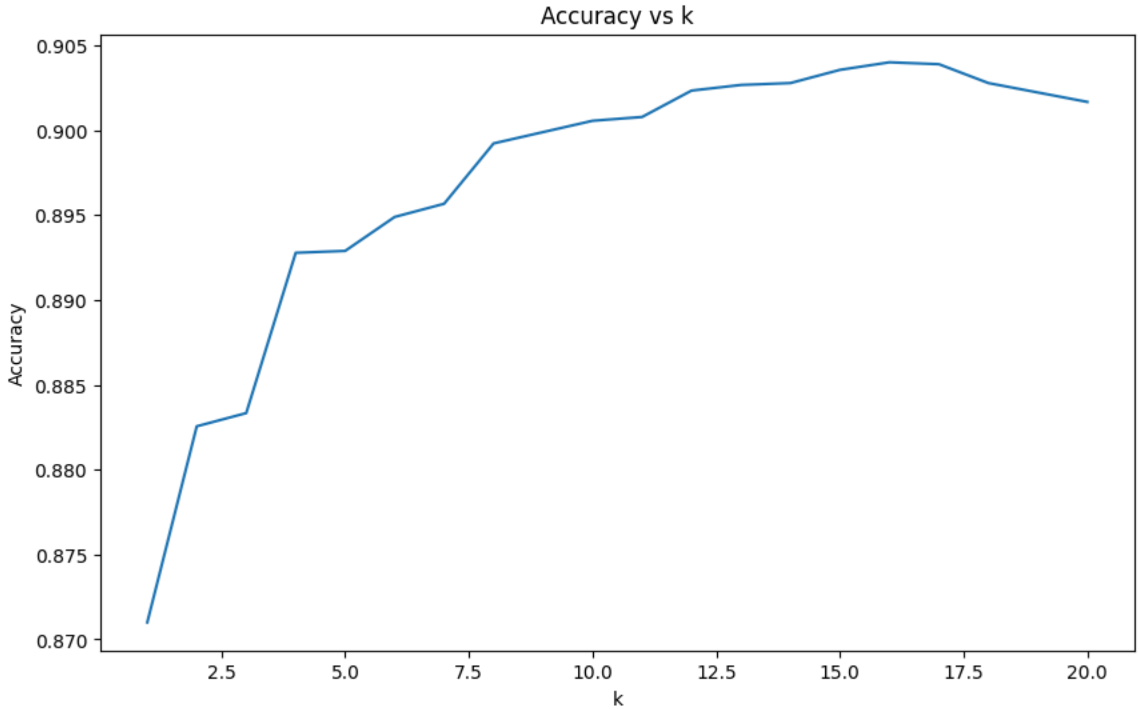
```
Naive Bayes - Training Set
Confusion Matrix (Accuracy 0.7456)

       Prediction
Actual     0     1
     0 19018  8992
     1   166  7824

Naive Bayes - Test Set
Confusion Matrix (Accuracy 0.7489)

       Prediction
Actual    0    1
     0 4772 2218
     1   42 1968
```

```
print("AIC:", AIC_score(y_test, nb_pred_test, df=scaled_X_train.shape[1]+1))
print("BIC:", BIC_score(y_test, nb_pred_test, df=scaled_X_train.shape[1]+1))
```

```
AIC: 13132.155721215886
BIC: 13231.625439204343
```

K Nearest Neighbors (KNN)

```
k_scores = []

# Loop to find the best k
for k in range(1,21):
  knn_model = KNeighborsClassifier(n_neighbors=k)
  knn_model.fit(scaled_X_train, y_train)
  acc = accuracy_score(y_test, knn_model.predict(scaled_X_test))
  k_scores.append((k,acc))


plt.figure(figsize=(10,6))
plt.plot([k for k,acc in k_scores], [acc for k,acc in k_scores])
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.title('Accuracy vs k')
plt.show();
```




```
# Choose best k
best_k = max(k_scores, key=lambda x: x[1])[0]
print("Best k:", best_k)
```

```
Best k: 16
```

```
# Final KNN model
knn_model = KNeighborsClassifier(n_neighbors=best_k)
knn_model.fit(scaled_X_train, y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=16)
```

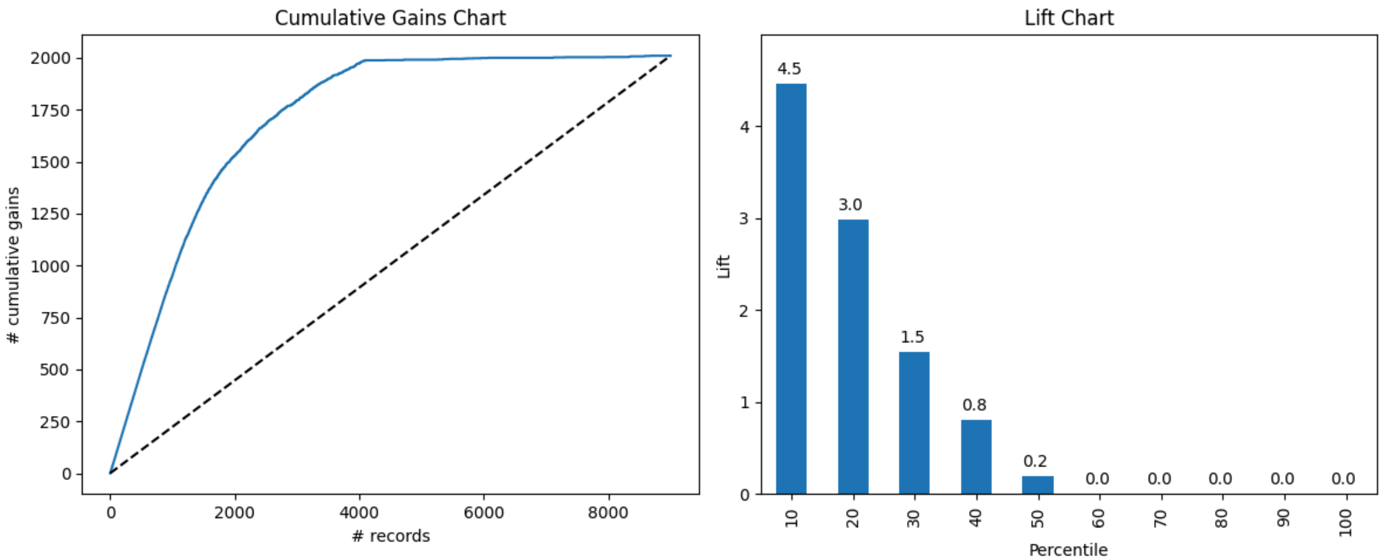
```
# Predictions
knn_pred_train = knn_model.predict(scaled_X_train)
knn_pred_test = knn_model.predict(scaled_X_test)


knn_probs = knn_model.predict_proba(scaled_X_test)[:, 1]

knn_results_df = pd.DataFrame({
    'actual': y_test,
    'p(1)': knn_probs
}).sort_values(by='p(1)', ascending=False)
knn_results_df.head()
```

	actual	p(1)
431	1	1.0
2265	1	1.0
43592	1	1.0
44347	1	1.0
14337	1	1.0

Next steps: Generate code with knn_results_df View recommended plots New interactive sheet

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
gainsChart(knn_results_df['actual'], ax=axes[0])
liftChart(knn_results_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title("Cumulative Gains Chart")
```

```
axes[1].set_title("Lift Chart")
plt.tight_layout()
plt.show()
```




```
# Evaluation
print("KNN - Training Set")
classificationSummary(y_train, knn_pred_train)

print("\nKNN - Test Set")
classificationSummary(y_test, knn_pred_test)
```

```
KNN - Training Set
Confusion Matrix (Accuracy 0.9117)

       Prediction
Actual     0     1
     0 27167   843
     1  2336  5654

KNN - Test Set
Confusion Matrix (Accuracy 0.9040)

       Prediction
Actual    0    1
     0 6769  221
     1  643 1367
```

```
print("AIC:", AIC_score(y_test, knn_pred_test, df=scaled_X_train.shape[1]+1))
print("BIC:", BIC_score(y_test, knn_pred_test, df=scaled_X_train.shape[1]+1))
```

```
AIC: 4478.2298100554035
BIC: 4577.6995280438605
```

Model Performance Comparison

```
def evaluate_model(name, y_true, y_pred):
    return {
        'Model': name,
        'Accuracy': accuracy_score(y_true, y_pred),
        'Precision': precision_score(y_true, y_pred),
        'Recall': recall_score(y_true, y_pred),
        'F1 Score': f1_score(y_true, y_pred),
        'ROC-AUC Score': roc_auc_score(y_true, y_pred)
    }


model_scores = [
    evaluate_model("Logistic Regression", y_test, logit_pred_test)
```

```
    evaluate_model("CART", y_test, cart_pred_test),
    evaluate_model("Naive Bayes", y_test, nb_pred_test),
    evaluate_model(f"KNN (k={best_k})", y_test, knn_pred_test)
]

model_comparison_df = pd.DataFrame(model_scores)
display(model_comparison_df.sort_values(by='F1 Score', ascending=False).reset_index(drop=True))
```

	Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC Score
0	KNN (k=16)	0.904000	0.860831	0.680100	0.759867	0.824241
1	CART	0.897222	0.821958	0.689055	0.749662	0.823068
2	Logistic Regression	0.887444	0.763617	0.718408	0.740323	0.827230
3	Naive Bayes	0.748889	0.470139	0.979104	0.635249	0.830897

We can clearly notice that the K Nearest Neighbors model with k=16 is the best performing classifier with an accuracy of more than 90% on the test set.

```
plt.figure(figsize=(8, 6))

# Logistic Regression
lr_probs = logit_reg.predict_proba(scaled_X_test)[:, 1]
lr_fpr, lr_tpr, _ = roc_curve(y_test, lr_probs)
plt.plot(lr_fpr, lr_tpr, label=f'Logistic Regression (AUC = {roc_auc_score(y_test, lr_probs):.2f})')

# Naive Bayes
nb_probs = nb_model.predict_proba(scaled_X_test)[:, 1]
nb_fpr, nb_tpr, _ = roc_curve(y_test, nb_probs)
plt.plot(nb_fpr, nb_tpr, label=f'Naive Bayes (AUC = {roc_auc_score(y_test, nb_probs):.2f})')

# KNN
knn_probs = knn_model.predict_proba(scaled_X_test)[:, 1]
knn_fpr, knn_tpr, _ = roc_curve(y_test, knn_probs)
plt.plot(knn_fpr, knn_tpr, label=f'KNN (AUC = {roc_auc_score(y_test, knn_probs):.2f})')

# CART
cart_probs = cart_model.predict_proba(final_X_test)[:, 1]
cart_fpr, cart_tpr, _ = roc_curve(y_test, cart_probs)
plt.plot(cart_fpr, cart_tpr, label=f'CART (AUC = {roc_auc_score(y_test, cart_probs):.2f})')

plt.plot([0, 1], [0, 1], 'k--')  # baseline
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves', pad=10)
```